Scanning or Simply Unengaged in Reading? Opportune Moments for Pushed News Notifications and Their Relationship with Smartphone Users' Choice of News-reading Modes

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News notifications on smartphones provide a convenient way to stay informed, but their delivery timing can influence user engagement. Despite this, research on the impact of notification timing on reading behavior remains limited. Therefore, we developed NewsMoment, a news aggregation app that monitors user reading patterns and sends news notifications. Our experience sampling study with 46 NewsMoment users revealed four distinct reading modes: typical, comprehensive, scanning, and unengaged. Deep reading, encompassing typical and comprehensive modes, more often occurred during self-initiated browsing rather than through pushed news. Interestingly, shallow reading modes - unengaged and scanning - showed varying prevalence, associated triggers, and engagement, despite their similarities. Importantly, unengaged reading persisted regardless of users' perceived moment opportuneness, whereas scanning reading was more common during inopportune moments. These findings suggest that identifying opportune moments for news reading may primarily reduce scanning reading, without substantially impacting unengaged reading.

CCS Concepts: • **Human-centered computing → Empirical studies in ubiquitous and mobile computing**.

Additional Key Words and Phrases: Mobile notifications; mobile receptivity; opportune moment; interruptibility; ESM

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1 INTRODUCTION

Numerous studies in the human-computer interaction (HCI) field have investigated news consumption, as it is a prevalent type of information consumed daily through technology [5, 6, 24, 35, 90]. In recent years, the ubiquity of mobile phones and mobile internet has made it not only convenient for users to access news on-the-go and at any time [21, 82, 97, 100], but also easier to share news [71]. This convenience has led to a gradual shift in news consumption from primarily desktop to mobile phones [21, 66, 68, 86], drawing increased attention from HCI researchers to investigate people's mobile news consumption and engagement behaviors further [16, 18].

A key feature of mobile phones is their ability to "push" news via notifications, in addition to users "pulling" news themselves [32]. This increases their volume of news consumption, as compared to those who disable push notifications [88]. A recent Pew Research report found that, among those Americans who were aware of push notifications, more than 40% said they "often" (12%) or "sometimes" (30%) used them for accessing news [63]. Additionally, news organizations are increasingly utilizing push notifications as a way to reach their audience [103]. However, this trend means that news-app users are receiving an increasing overall quantity of notifications, which are essentially interruptive and distracting [12, 60, 67], especially when they are sent at inopportune moments [62, 77, 80]. Although short-form reading, including news reading, often takes place in short interludes between, or even within, other activities [25], this does not necessarily mean that mobile phone users will be receptive to pushed news at any time. In particular, people's available cognitive, attentional, and time resources for reading news articles fluctuate throughout the day and from one activity to another [29]; and, when they are multitasking or their attention is otherwise divided, their news-reading performance (i.e., comprehension and counter-arguing) can also be lower [44, 49]. Furthermore, prior research has linked perceived limited time and cognitive resources to a lower likelihood of detecting inaccurate news information. Bago et al. [4] found that participants were more likely to believe false headlines when they had time constraints and concurrent working memory loads. This difference was attributed to quick judgments and intuitive responses to information encountered without systematic processing, which has also been associated with a lower likelihood of detecting misinformation within articles [79]. To prevent users from processing news shallowly and quickly, one reasonable way, then, is to send pushed news at moments when smartphone users would be more likely to thoroughly process news articles, namely, *opportune moments* for reading pushed news. However, while there is a growing body of literature on identifying opportune moments for delivering various types of notifications (e.g. [13, 14, 29, 37, 50, 52, 80, 84, 97, 99]), prior research has not established a connection between the perceived opportuneness of the moment for pushed-news notification and how smartphone users would typically read news on their phone, namely, their news *reading modes*. Therefore, it is unclear whether receiving pushed news at perceived opportune moments is more likely to result in more in-depth reading of the associated news articles, or conversely, whether receiving it at perceived inopportune moments is less likely to result in in-depth reading of such articles. Our aim is therefore to fill that research gap, guided by the following three research questions:

- RQ1: What are the common news reading modes on smartphones, and how pervasive is shallow/deep reading, particularly of pushed news?

- RQ2: How does the perceived opportuneness of the moment for pushed-news notification delivery affect the likelihood that shallow/deep reading will ensue?
- RQ3: How would smartphone users perceive themselves' news reading when they adopt a shallow or deep news-reading mode, including: a) the extent of their own news-reading coverage, engagement, and b) the credibility of the news they are reading?

To answer these research questions, we adopted a mixed-methods approach. We developed an Android news app called NewsMoment that aggregates news from nine popular news apps and delivers pushed news notifications. The app logs its users' reading behavior and phone-sensor data, and delivers ESM (Experience Sampling Method) questionnaires to capture users' contextual information about specific instances of news reading and self-assessment of their reading engagement, comprehension, and perceptions of the news items they read, and perceptions of the opportuneness of particular moments for reading the news. We invited 46 people to use NewsMoment for 14 days and observe their experiences and behaviors. This paper makes four crucial contributions:

- This study identified four distinct modes of reading news items on a smartphone news app: *comprehensive, typical*, *unengaged*, and *scanning* , and found that the shallowest modes - unengaged and scanning - were more likely to be triggered by push notifications sent by the news app than by self-initiated news reading in the app. In contrast, the deeper reading modes - comprehensive and typical - were more likely to occur when the news reading was self-initiated in the app.
- It establishes that receiving pushed news at perceived opportune moments was more likely to result in deep reading of the associated news articles compared to when receiving during perceived inopportune moments. Additionally, it shows that opportune moments for reading entire news articles were similar to opportune moments both for receiving notifications and for checking article's titles in terms of their likelihood of resulting in deep news reading.
- It establishes that these two shallow reading modes are distinct from each other, including their reading patterns, prevalence, associated main trigger, and self-rated reading engagement and comprehension. In particular, unengaged reading mode was found prevalent irrespective of the opportuneness of the moment, whereas scanning reading was more common during inopportune moments.

2 RELATED WORK

2.1 Mobile News Consumption

As long ago as 2018, the percentage of Americans who obtained news from a mobile device had reached 88% [31]. In short, people no longer consume news at fixed times or in fixed places, but can read it more actively and flexibly [21, 101, 104]. Moreover, outlets that offer mobile news seem to be progressively occupying more of readers' otherwise-unallocated time [9]; and spatially, news consumption's transformation from desktop-based to mobile also implies a greater variety of contexts in which news reading will occur, making it more likely to be subject to environmental factors [25, 69]. It has been reported that mobile news readers' engagement levels and psychological factors (e.g., negative experiences) [55] influence their news-related behaviors and satisfaction. Nam et al. [65] also showed that leisurely reading can lead to very different reading behaviors, because readers select the material themselves and may not have any particular reading goals in mind, at least initially. Reading news while multitasking also negatively affects people's comprehension and ability to make counter-arguments [44].

Given that reading on mobile devices differs fundamentally from reading on a desktop (e.g., due to the former's smaller screen size and unique interaction methods) [98], a growing body of literature is focused on patterns of news reading on mobile devices. Some of these studies have used self-report methods to explore mobile users' reading behavior [20, 58, 64]. For example, Molyneux [64] conducted two online surveys to measure news consumption across platforms, and found that – as compared to reading news on other devices such as computers and tablets – mobile news reading is shorter, more frequent, and spread more widely across the hours of the day. The locations of news consumption have also been captured through self-report methods [20, 97]. Van Damme et al. [97] collected personal diaries and conducted face-to-face interviews and reported that the majority of news consumption on mobile devices took place at home, either in the morning or the evening.

However, studies of such topics that rely on self-reported data may not precisely represent actual usage [7, 11, 19]. For example, Boase and Ling [7] examined the validity of self-report data by comparing it against server log data, and found that the former was of low criterion validity. Moreover, people's self-reports tend to overstate the frequency of their mobile-device use [45, 64].

2.2 News Reading Behavior

To obtain a more detailed and reliable account of news-reading behaviors on mobile devices, some researchers have used logs to record them. For example, Nam et al. [65] found that touch-location data was useful in distinguishing a user's level of familiarity with a topic, while reading-time and scrolling data could be used to differentiate between reading content contextually or literally. Similarly, Homma et al. [39] used log data to identify a relation between short dwell time in news articles and low user interest; and Grinberg [36] showed that article dwells time was the single best predictor of reading engagement. Carreira et al. [10] logged users' news-article reading behaviors and showed that it was feasible to recommend content based on such behaviors. Similarly, Constantinides et al. [20] logged their participants' interactions with a mobile news app and demonstrated that logs could be used to build classifiers that recognized reader types. Different reading patterns can also lead to variations in reading performance. Li et al. [53], for example, showed that scrolling was associated with a better memory of short texts, and lower mental and temporal demands, but greater visual fatigue. By collecting more reading behavioral data, researchers could possibly know how people read news and distinguish different news reading modes.

Lagun and Lalmas [48] captured how much time people spent on different parts of news articles on websites (i.e., the header, body, and comments section) during a single reading session on desktop devices; then, they used clustering with reading patterns to identify four engagement levels: bounce, shallow engagement, deep engagement, and complete engagement, from which different news-reading modes could be inferred. Likewise, Grinberg [36] used several features, including dwell time, reading depth, and average scrolling speed, to cluster five different clusters: scan, read, read(long), idle, and shallow. Both of these two studies [36, 48] identified two general reading patterns, including one that represents a complete and deeper reading, and the other representing shallow reading, characterized as a reading that takes relatively short reading time and on little content. As a result, when adopting this mode of reading, the reader is regarded as incompletely processing the news information. However, in Grinberg's [36] study, shallow reading is found as less than 2% of the page having been viewed, quite different from the less-than-50% standard for shallow engagement [48].

Notably, while both studies present readers' news reading patterns, they were conducted in either a desktop context [48] or across both mobile and non-mobile devices [36]. As such, the applicability of the reading modes identified in these studies to mobile devices is questionable. Mobile phones and desktops differ in various ways that make news reading behavior and situations distinct from one another, including context variability (mobile devices enabling news reading anytime and anywhere vs. desktops being confined to specific and static locations) and device affordance (e.g., screen size, interaction capability) [26, 27, 87, 102], which may affect the amount of interaction and time needed to read the entire news article. While we do not claim that these differences lead to entirely different sets of reading modes, we acknowledge that reading instances observed in our dataset may not necessarily directly map to the reading patterns found in the two previous studies. Therefore, we employed a bottom-up and unsupervised clustering approach to identify reading patterns within our dataset. Indeed, we found numerous differences between the identified reading modes, which are linked to the more frequent task-switching and short-lived interaction on mobile phones. This resulted in the overall shorter interaction duration with news items and the absence of certain reading modes found in previous work in our studies. Furthremore, in addition to identifying reading behaviors, our study also links them to the perceived opportuneness of the moment by collecting this perception via experience sampling method and linking it to logged reading behavior. This allowed us to show that deeper reading was more likely to occur when pushed news was delivered at times that participants perceived as opportune for pushed news.

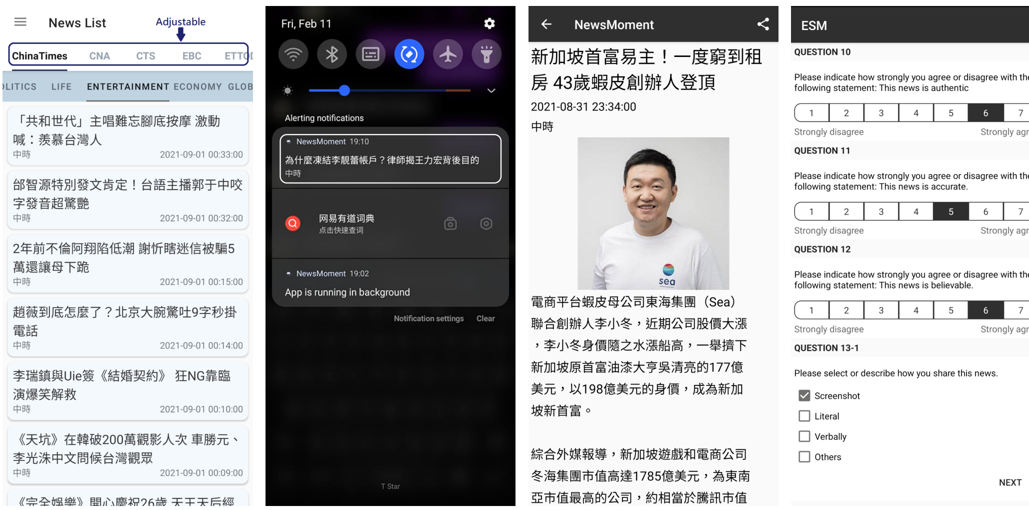
2.3 Opportune Moments for Delivering Content

Interruptibility research has been carried on for decades, with the wider aim of reducing interruptions in workplaces [70, 107] and desktop environments [23, 40, 43]. In recent years, considerable research attention has shifted to mobile receptivity [14, 38, 106]. In particular, opportuneness describes whether a given moment is suitable for a person to perform a particular action [78]. Various other terms for and sub-types of opportune moments have been proposed, including interruptible moments [14, 38, 56, 59, 93, 106], break-points [1, 14, 33, 42, 72–75, 77, 85, 89], transitions [92], receptive moments [34, 61, 94], and moments when users would be attentive [28] or responsive [51]. However, all of this research shares the aim of identifying, characterizing, and predicting good moments for people to receive notifications [80, 81, 95], including but not limited to messaging notifications [78] and ads [80, 99]. Research that explores moments for smartphone delivery of other pushed content that requires more engagement than notifications do is also growing, and so far has looked at questionnaires [80], behavioral interventions [50, 52, 84], mini-games [80], and learning materials [30], among other such content. However, different types of pushed content entail different types of actions, and thus, opportune moments for receipt of one type of it may not be applicable to other types [80]. Recent research on opportune moments for crowdsourcing tasks, for instance, suggests that different moments are perceived by users as suitable for different types of micro-tasks [14].

Thus far, however, we have little knowledge of opportune moments for reading pushed news. Okoshi et al. [76] conducted one of the few studies to date aimed at detecting interruptible moments for pushed-news delivery. Adopting Yahoo, one of the most popular news apps in Japan, as their experimental material, they used mobile sensing and machine-learning techniques to detect users' breakpoints and then sent out news notifications during them. Okoshi et al.'s detection approach achieved success, leading to a 60% increase in click rate, but they did not measure the level of engagement or the depth of reading for their participants. While current research has not thoroughly explored these topics, our paper aims to fill this gap by examining the relationship between the timing of push news notifications and smartphone users' reading behaviors.

3 METHODOLOGY

Both the quantitative and qualitative aspects of this mixed-methods study relied on our Android news app, NewsMoment, which allowed the participants to read the news; logged their reading behavior and phone-sensor data; and delivered ESM questionnaires aimed at capturing specific news-reading instances' contexts, along with their subjective experiences of such instances, including



(a) News List (b) Pushed News Notification (c) News Article (d) ESM Questionnaire

Fig. 1. Our news app's (a) main page with news-source bar and category bar, (b) pushed news notification with news title and news source, (c) news-article presentation with the title, publication time, source, image, and content, and (d) ESM questionnaire displaying questions related to the perceived credibility of news

self-assessment of reading outcomes and the perceived opportuneness of reading a piece of news at a particular moment. Further details are provided below.

3.1 NewsMoment

NewsMoment aggregates news from nine popular news apps in Taiwan and delivers news notifications to users, enabling them to access news from their preferred news outlets in the same way they normally would. To capture participants' news-reading behaviors and experiences as fully as possible, without skewing those behaviors or experiences, our design goal was for NewsMoment to closely replicate the participants' usual news apps, including their user interfaces (UIs) and their patterns of pushed-news notification delivery.

3.1.1 Core Features and User Interface. NewsMoment's UI is presented in Figure 1. We compared the most popular news apps in Taiwan and identified their common design features. The design of NewsMoment's UI was based on these features so that it would look familiar to most of our participants. As shown in Figure 1a, our UI included a nested tab bar. The top tab bar is the news sources bar, which contains a list of the nine selected news sources that the app aggregates news from. NewsMoment users can determine which of these nine sources they want to receive news notifications from. With Figure 1b serving as an illustrative example of our push notification.

The second tab bar from the top is the news classification bar. The list of news-classification tabs that appears under each news source is identical to that organization's own such lists. Again, the purpose of this was to maximize the perceived similarity between reading news in NewsMoment and reading the same news on authentic news apps. News content was scraped from the website of each news organization every 10 minutes, and included images, text, and ad text; all of this was then displayed in NewsMoment as seen in Figure 1c. Also, it illustrates how the user is directed to the app's built-in sharing function, whereby Android users can share the news they have read via various other apps, e.g., Facebook, LINE, and Messenger.

3.1.2 Pushed News Notifications. To prevent participants from receiving duplicate notifications about the same news item, NewsMoment suppressed pushed notifications from users' existing news apps, ensuring that all the pushed news notifications they received were from NewsMoment. Thus, an important mission when designing NewsMoment was to ensure that it created sets of pushed news notifications that were identical to those produced by each of its users' existing news apps, such that no one would feel they had missed any such notifications due to having installed NewsMoment on their phone during the study. To achieve this, the research team installed all nine of the selected news apps on two experimental smartphones and collected their pushed news notifications. Once the NewsMoment on these phones detected such notifications, it collected their linked news items' titles and source names and used those pieces of information to query news articles from our research server that stored scraped news, as discussed above. The server then compared the notification's title against news titles using Gestalt pattern matching [83] and found the most similar one using a similarity score. The news item that received the highest similarity score (which should be at least 0.5) was pushed to the participants' smartphones.

3.1.3 Data Collection. NewsMoment logs its users' news-browsing and news-reading behaviors. Specifically, it tracks the position of the user's *viewport* in the news, inspired by prior analytical work [47, 48]. Each viewport is defined as the line of the content presented on the user's screen, the number of viewports largely depends on both the size of the screen and font size. Normally each screen contains 20-25 viewports.

First, each line of a news item's text (including its title, source, published time, and context) and each image in it is defined as a viewport, and NewsMoment records which blocks/units are visible on the screen per 0.1 second period. The app also logs users' actions such as scrolling, entry, exit, and use of the Android built-in sharing function. These logs allowed us to track what area within a news item each of our participants was focused on at any given time, from which we were able to generate advanced metrics such as dwell time of each viewport, scrolling speed (changes in viewports per second), and standard deviations in scrolling speed. In addition, NewsMoment logged our participants' actions during article reading, including detailed scroll gestures; whether the article was accessed through notifications or not, and shared or not; total dwell time. Finally, NewsMoment collected sensor data that might later help us identify opportunities in the future, as in previous work (e.g. [80]).

3.2 ESM Study

An Experience Sampling Method (ESM) study was conducted via NewsMoment to capture participants' experiences of specific news-reading instances, contexts, self-assessment of outcomes, and perceptions of the opportuneness of reading moments as described below.

3.2.1 ESM Mechanism. Our research app, NewsMoment, was installed by the participants who configured it by choosing a window longer than 12 hours every day to receive ESM questionnaires. The app determined the ESM-prompt schedule for the whole study period. ESM prompts were sent at random intervals with a minimum of one hour and a maximum of 12 questionnaires per day. To reduce inaccurate self-reporting due to recall bias, ESM prompts were dismissed if not engaged within 15 minutes. The app checked the participant's current news use before deciding whether to send out an ESM questionnaire according to the rules mentioned in the next paragraph. To minimize inaccurate self-reporting due to recall bias, NewsMoment only sampled reading instances and news notifications that occurred within 30 minutes prior to the sampled moment.

With regard to what was sampled, our first priority was news reading. Two ways to read news on NewsMoment were considered: 1) clicking on a pushed news notification, and 2) entering a news item via the app's browsing interface. We expected that these two types of reading could be associated with different reading patterns and thus, an algorithm was designed to balance the sampling across them. If both types of reading had occurred within the previous 30 minutes, NewsMoment sampled whichever type that it had not sampled from the same participant in the immediately preceding sampling round. If only one type of reading had occurred within that same window, it sampled that one. If no reading behaviors had occurred in the previous 30 minutes, but a pushed news notification had, it sampled that notification. If neither any reading instance nor pushed news notification had occurred, the pre-scheduled ESM prompt was not sent out.

3.2.2 ESM Questionnaire. Two types of news-reading instances were associated with different ESM questionnaires. A separate questionnaire was used to ask about the moment of notification arrival and the moment of entering the pushed news, as participants may not immediately read the news after receiving the notification. The ESM questionnaire for pushed news began by displaying information about the notification, including the title and time of arrival, to remind the participants about the news notification they recently read. The rest of that questionnaire contained four parts: 1) the context of the notification-receiving moment, 2) the context of the news-reading moment, 3) self-assessment of reading performance and purposes, and 4) news-sharing behaviors. The other variant of the questionnaire did not ask any questions related to notifications. Cases where participants were aware of the notification but did not click to read the news or were not aware of the sampled news at all, were also considered. This resulted in variations in the overall questionnaire flow and length of the questionnaire (Max = 39, Min = 1).

In the notification-context section (when included), the participants were asked to estimate 1) how much time they had spent reading the news item [29], 2) their present activity [54, 105], and 3) their activity's complexity at the moment of receiving the notification [62] on a seven-point Likert scale, followed by three questions about the user-perceived opportuneness of the moment for 4) receiving the notification, 5) checking the article's title, and 6) reading the entire news article, inspired by the three-stage notification handling stage proposed by [95], such as "When receiving the pushed news notification at ..., to what extent do you agree that the moment was suitable for receiving the notification?." The news-reading context section (which was present in both questionnaire variants) followed the same flow and set of questions. If both context sections were included in an ESM questionnaire, to decrease the burden on the respondents, they were allowed to declare that the moment when they read the news was the same moment at which they received the notification and skip the news-reading context section if they made such a declaration.

In the self-assessment part (both questionnaire variants), the participants assessed their reading performance and purposes. Because repeat reading could have different effects from first-time reading, they were first asked if it was the first time they had read the sampled news content. Then, they were asked to rate the coverage of their reading on a 10-point scale, and this was followed by eight questions covering their level of engagement with [57], comprehension of [44], interest in the news article, relevance, complexity, and message credibility (authenticity, accuracy, and believability) [3] on a 7-point Likert scale. Sample questions included: "Subjectively, what percentage of the news content do you think you read regarding this news article?", "What is your level of engagement while reading this news article?", and "Please indicate the degree to which you agree or disagree with the statement that the news is authentic." Finally, they were asked about their reading purposes and triggers; the contextual factors they thought had influenced why they read the sampled news in the chosen way; whether they shared the news item or not; and why and how they shared the news if they said they had done so, sample questions including: "What was your purpose(s) for reading that news?" and "Following the previous question, what factors influenced your decision to adopt that reading behavior?" Figure 1d shows the sample screenshots of the ESM questionnaire.

To ensure the feasibility of the study, we conducted a pilot study with 7 participants to test the time required to complete the questionnaire and the effectiveness of the ESM delivery mechanism. We identified and removed non-essential questions, resulting in a focus on core questions in the data collection. Some of these questions were not included in the final analysis and presentation because they were out of the scope of the current paper. The pilot participants, took an average of 85 seconds (SD = 81, Mdn = 61) to complete each questionnaire, which was within the typical duration for completing an ESM questionnaire, i.e., less than 2-3 minutes (e.g., [8, 17, 22]). In the formal study, participants took an average of 58 seconds (SD = 186, Mdn = 57) to complete each questionnaire.

At the end of each day, a diary questionnaire was issued one hour before the end of the window participants had set for receiving questionnaires, which contained information about the ESM they had answered and four questions about their overall reading experience of that day. In this paper, we did not analyze the data from their diaries.

3.3 Study Procedure

Prior to data collection, due to the COVID-19 pandemic, the researchers explained the study procedure via video conferencing and asked the participants to sign their consent forms online. Then, the researchers remotely helped them to install the app on their phones, and checked if there had been any installation or compatibility problems by setting several tests during the experiment explanations. Then, the researchers briefly introduced NewsMoment and helped them finish adjusting its settings. NewsMoment started delivering ESM questionnaires on the first day following successful installation and continued doing so for at least two weeks. When a participant was found not participating actively in the study on a specific day, they were informed to continue their participation for an additional day to ensure that we could collect 14 full days of data on their news reading behavior. The data from these interviews has been analyzed and reported in a separate study.

At the end, for every ESM that they completed, the participants received NT 14 (approximately US 0.50), and for being interviewed, they received an additional NT 150 (approximately US 5).

3.4 Recruitment and Participants

The participants were recruited through social media advertisements. They were required to be 1) currently using news-aggregator apps, such as Google News or Yahoo News, or 2) receiving pushed-news notifications in their daily lives. Initially 46 individuals participated in the study; three participants had to withdraw from the experiment due to technical issues with their smartphones. Of the remaining 43 participants, 26 reported reading pushed news 1-3 times daily, 10 reported reading pushed news 4-6 times daily, and 7 reported reading pushed news more than six times daily. 22 were students, and the rest had a variety of occupations. They were aged from 20 to 43 (M = 27.1, SD = 6.5); 18 were females and 25 were males. All participants participated in the study for at least two weeks.

3.5 Data Cleaning and Analysis

A total of 4,010 ESM questionnaires were received, and 13,711 news-reading instances were logged. The participants completed an average of 87.1 ESM questionnaires (Max = 144, Min = 26, SD = 28.99) during the study and 6.1 ESM surveys per day (SD = 2.8), respectively. During analysis, we only considered ESM instances where participants reported actually reading the sampled news item in NewsMoment. Any sampled news that participants reported as not having read on NewsMoment was excluded from the analysis. This filtering process resulted in 1,506 remaining ESM responses. Out of these, 138 (9.2%) were found to be inconsistent with phone logs and were excluded from the data analysis. An additional 135 ESM responses were excluded as the participants indicated that they had already read the news item, thus their reading behavior may have differed. Our final ESM dataset for analysis consisted of 1,233 ESM responses, with an average of 23.7 questionnaires per participant. (Max = 113, Min = 0, SD = 28.7).

A total of 13,711 news-reading instances were recorded by NewsMoment. Instances where the dwell time was too short (476 instances below 1 second) or too long (five instances exceeded 10 minutes) were removed as accidental entries and outliers, respectively. Additionally, 489 instances where the system logs showed that the page did not load the content were removed. The final dataset consisted of 12,746 news-reading instances (M = 296.4, Max = 2,372, Min = 23, SD = 379.6). Out of these instances, 3,007 (23.59%) were entered from the browsing interface in NewsMoment, and 9,739 (76.41%) were entered from pushed news notifications.

Statistical analysis was conducted using mixed-effect regression analysis to examine the effect of factors of interest, such as the effect of reading mode on reading outcome. For binary predicted variables(e.g. examining likelihood), mixed-effect logistic regression was used. Mixed-effect models were adopted as every participant contributed repeated observations. A chi-square test of independence was also employed to examine the associations between pairs of factors, such as the initiation of news reading and the occurrence of a particular reading mode.

4 RESULTS

4.1 Mobile News Behavior

This section begins with our findings about overall patterns of news reading on NewsMoment. Then, it describes each of the four reading modes we identified using clustering analysis of 12,746 reading instances.

4.1.1 Overall Mobile News Behavior. On average, our participants spent 24.7 seconds on each news article on NewsMoment (SD = 43.6), at an average scrolling speed of 2.5 viewports/sec (SD = 5.1). Participants' scrolling speeds within a news article also varied. The average standard deviation (SD) of their scrolling speed was 4.0 viewports/sec (SD = 5.9), suggesting strong variation in scrolling behaviors within an article. The numbers of scrolls per news article were also diverse (M = 6.7, SD = 9.3). Given the diversity of participants' reading behaviors, while using NewsMoment, clustering techniques were used to distinguish them, as explained below.

4.1.2 Identifying Reading Modes on NewsMoment using Clustering. As mentioned earlier, we opted to find reading patterns within our own dataset using the clustering technique instead of directly mapping our reading instances to previously discovered reading modes [36, 48]. This decision was based on our uncertainty about which patterns of news reading found in the desktop environment would be present or absent in our dataset and whether the methods used to distinguish those patterns could be employed to discern reading patterns occurring on mobile phones. Therefore, we carefully examined all the data collected from participants and reviewed the two studies with similar attempts [36, 48] to classify news-reading patterns. Based on these two studies, we selected five features that described behavior within a reading instance for clustering purposes. They were *dwell time*: the duration that the user stayed in news article; *coverage*: the percentage of the viewports at which users stayed longer than 1 sec; *# of scrolls*: the count of scrolls used; *scrolling speed*: the number of viewports per second; and *SD of speed*. Importantly, the feature of Speed SD has not been used in previous studies; we included it in our research because we found that it effectively distinguished between instances of stable reading and instances where users quickly scanned news articles based on our data. Also note that coverage differs from page depth [36] in that the former

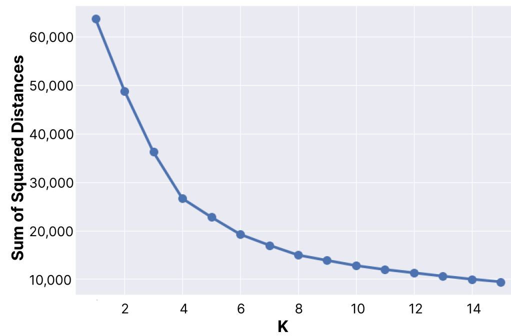


Fig. 2. Results of the elbow method for optimal K

takes account of the amount of time participants stayed at each viewport, whereas the latter only involves the percentage of the viewports at which users stayed.

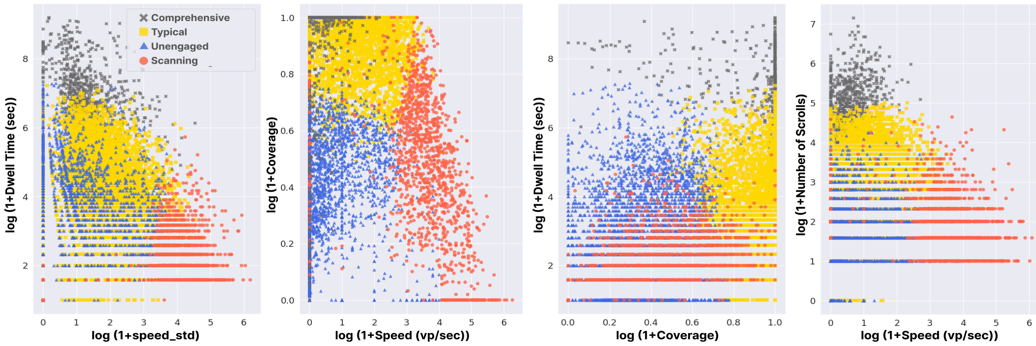
We used the K-means clustering algorithm [91] to distinguish among participants' reading behaviors. For this purpose, all of the features mentioned in the previous subsection were standardized. To find the optimal number of clusters K, we iterated K from 1 to 15 and used the elbow method [46] to choose a K that minimized the sum of the square distance from each point to its assigned center. As Figure 2 shows, the elbow point was at $K = 4$.

4.1.3 Comparison of the Four Reading Modes. To answer RQ1, figure 3 shows the resulting four clusters, and Table 1 provides the descriptive statistics of those clusters. Specifically, the figure illustrates the distribution of the points projected in a two-dimensional space on a logarithmic scale. Each point in the figure represents a news-reading instance, colored according to the cluster to which it was assigned. Figure 3b, for instance, shows how the four clusters vary in terms of coverage and scrolling speed, while Figure 3c indicates that high dwell time did not necessarily lead to great coverage. The high distinctiveness among the four reading modes can also be seen from Figure 4's boxplots of the features.

Reading Mode	**# of Scroll**	**Speed**	**Speed SD**	**Dwell Time**	**Coverage**	**Page Depth**
Typical (53.0%)	7.26 (*SD* = 5.47)	1.61 (*SD* = 1.76)	3.52 (*SD* = 3.09)	21.74 (*SD* = 19.28)	0.94 (*SD* = 0.12)	0.98 (*SD* = 0.08)
Comprehensive (7.0%)	29.10 (*SD* = 18.23)	0.51 (*SD* = 0.58)	1.99 (*SD* = 2.13)	134.14 (*SD* = 98.15)	0.93 (*SD* = 0.18)	0.95 (*SD* = 0.15)
Unengaged (29.8%)	1.37 (*SD* = 2.28)	0.65 (*SD* = 1.66)	1.07 (*SD* = 2.26)	11.08 (*SD* = 17.01)	0.29 (*SD* = 0.16)	0.44 (*SD* = 0.24)
Scanning (10.2%)	3.59 (*SD* = 2.90)	13.65 (*SD* = 9.29)	16.27 (*SD* = 9.37)	4.86 (*SD* = 4.15)	0.41 (*SD* = 0.24)	0.96 (*SD* = 0.13)

Table 1. The four identified reading modes with their descriptive statistics

Cluster 1: Typical (53.0%, n = 6,750) was the most prevalent pattern of the participants' reading on NewsMoment. It tended to be moderate in all dimensions, and lacking in distinctive characteristics. When using this reading mode, 87.6% of participants scrolled to the end of the article in question,



(a) Speed *SD* and Dwell Time (b) Speed and Coverage (c) Coverage and Dwell Time (d) Speed and Number of Scrolls

Fig. 3. Two-dimensional scatter plots of the clustered data across the five dimensions on a logarithmic scale

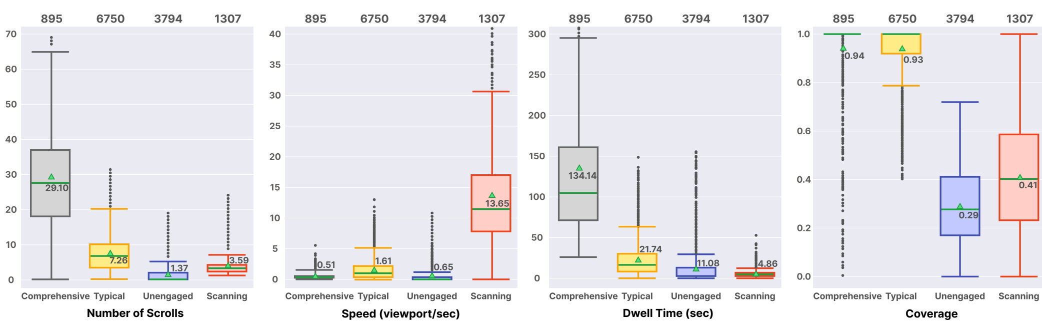


Fig. 4. Four box plots representing differences in the distribution of each reading mode on four features. The lines on the box plot represent the lower quartile, median, upper quartile, and the interquartile range of the feature named below it

and 65.6% of them achieved 100% coverage of it. This mode also had the second-longest average dwell time, at 21.7 sec.

In *Cluster 2: Comprehensive (7.0%, n = 895)*, the participants read the news thoroughly and carefully: with 84.8% scrolling to the end of the article, and 77.1% achieving 100% coverage. Dwell time was by far the longest among all modes (134.1 sec, *SD* = 98.2), and 6.2 times longer than the mode with the second-longest dwell time, i.e., typical Reading. In addition to dwell time and coverage, the comprehensiveness of the reading conducted in this mode is reflected in the number of scrolls, which was four times higher than the nearest contender, typical reading.

Cluster 3: Scanning (10.2%, n = 1,307) indicated rapid and sporadic news reading characterized by quick scrolling, and reflective of insufficient processing and shallow reading. In it, the average reading coverage was only 41%, though 85.6% reached the end of the article. Individual variation in scrolling speeds varied sharply, seemingly because the participants sporadically and briefly lingering at a certain part of an article before proceeding to scroll.

Cluster 4: Unengaged (29.8%, n = 3,794) was the second most prevalent reading mode. In it, participants opened a news article, but were not really focused on reading it, with more than half of them (50.7%) not scrolling at all. Only in 31% of cases did they scroll even to the halfway point. Consequently, this mode was also marked by the lowest coverage, lowest number of scrolls, and lowest page depth. Participants in this mode generally left the news soon after entering it, but

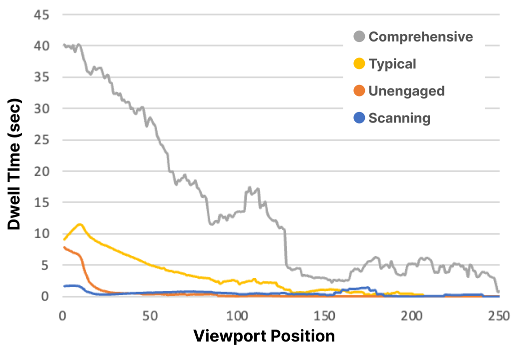


Fig. 5. Average dwell time across viewport positions, by reading mode

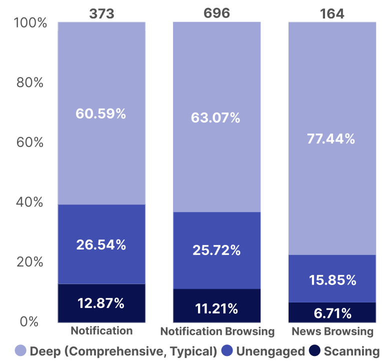


Fig. 6. Reading modes across three types of initiation, i.e., Notification Triggered, Self Notification Browsing, and Self News Browsing (The numbers of data points are displayed above each bar.)

occasionally remained on the first page without taking any action, likely due to inattention; and this behavior caused relatively large variance in their dwell times. Along with scanning, we deem unengaged reading to be a shallower reading mode that induces insufficient processing of news articles.

Inspired by [47, 48], Figure 5 presents how the four reading modes differed in terms of the participants' average dwell time at each viewport position. Unlike in the two deeper reading modes, the dwell time for scanning was close to zero until the participants reached certain points in the text that they desired to scrutinize. Participants who adopted unengaged Reading, on the other hand, rarely scrolled beyond the first 20 viewports (approximately the first page).

4.1.4 Initiation of News Reading: News App vs. Pushed News. We next investigated whether a particular reading mode was more likely to be associated with certain triggers. In the ESM, participants were asked about what triggered their exposure to the sampled news, and the selected triggers were 1) *Notification*: news reading soon after receiving a pushed news notification; 2) *Notification Browsing*: news reading initiated by participants themselves while browsing notifications in the notification drawer; and 3) *News Browsing*: news reading initiated by participants themselves while browsing news in NewsMoment. We primarily relied on ESM data for this purpose since the logs from NewsMoment only allowed us to determine whether users accessed news articles within the app or via pushed news notifications, i.e., they did not differentiate between notification browsing and notification. Among the ESM responses associated with a particular reading mode, the distribution of the four reading modes was as follows: comprehensive: 5.6%, typical: 58.2%, unengaged: 25.3%, and scanning: 10.9%. These percentages are similar to those of the logged reading modes presented in Table 1. Due to the small number of ESM responses associated with comprehensive reading (5.6%), we merged these responses with the typical reading category for the following subsections, which did not focus on distinguishing between these two modes. However, despite the small proportion of scanning responses, we decided not to merge them with the unengaged reading mode because we observed distinct characteristics between the two, which led to different implications for the detection of opportune moments (we will discuss this in more detail later). As Figure 6 shows, deep news reading, encompassing both comprehensive and typical modes, was more likely to occur during news browsing-triggered sessions (77.4%) compared to other initiation types (Notification: 60.59% and Notification Browsing: 63.07%); conversely, shallow reading modes,

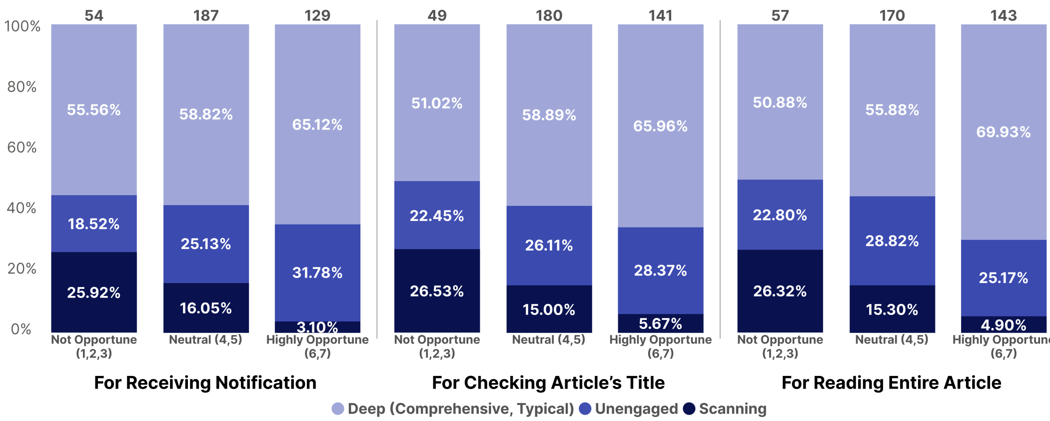


Fig. 7. Prevalence of the reading modes across moments perceived as opportune (or not) for three different news-related activities (The numbers of data points are displayed above each bar.)

unengaged and scanning, were more prevalent when news reading was notification-triggered (Total: 39.4%, unengaged: 26.5%, scanning: 12.9%) and initiated by notification browsing (Total: 36.9%, unengaged: 25.7%, scanning: 11.2%) than when it was initiated by news browsing (Total: 22.6%, unengaged: 15.9%, scanning: 6.7%), respectively. In other words, participants demonstrated a higher level of thoroughness in their news reading when they self-initiated and actively selected the articles they read while using a news app. A chi-square test of independence showed that these associations were statistically significant (χ^2 = 15.01, p < .001).

In the subsequent sections, our analysis will center on the instances of news reading that were triggered by notifications, since in these instances participants' news reading was the result of receiving push notifications rather than self-initiating it. This focus allows our analysis to better align with our primary goal of investigating the relationship between the moment of pushed news notifications and participants' news reading behavior. To keep the language simple, we will refer to these instances as "reading pushed news" or similar for the remainder of the text.

4.2 Influence of Moments on Pushed News Reading

To answer RQ2, we investigated whether receiving pushed news at perceived opportune moments is more likely to result in more in-depth reading of the associated news articles than at perceived inopportune moments. As a reminder, in the assessment of the moment, participants were asked to indicate on a 7-point Likert scale whether they felt that the timing of the received news notifications was opportune for three different actions: receiving the notification, checking the article's title, and reading the entire article.

4.2.1 Influence of Perceived Opportuneness of the Moment. Figure 7 displays the distribution of participants' reception to the sampled pushed news, based on their perceived opportuneness of the moment for three kinds of actions, each of which was classified into three levels: highly opportune (6,7), neutral (4,5), or inopportune (1,2,3). This classification puts a higher bar for a moment being regarded as opportune than being regarded as inopportune for news reading, as we assumed that reading news requires users to have a higher receptivity to process a news article fully.

As Figure 7 shows, participants were more likely to adopt deep reading at opportune moments than otherwise across all three kinds of opportune moments (for receiving news notification, Z =

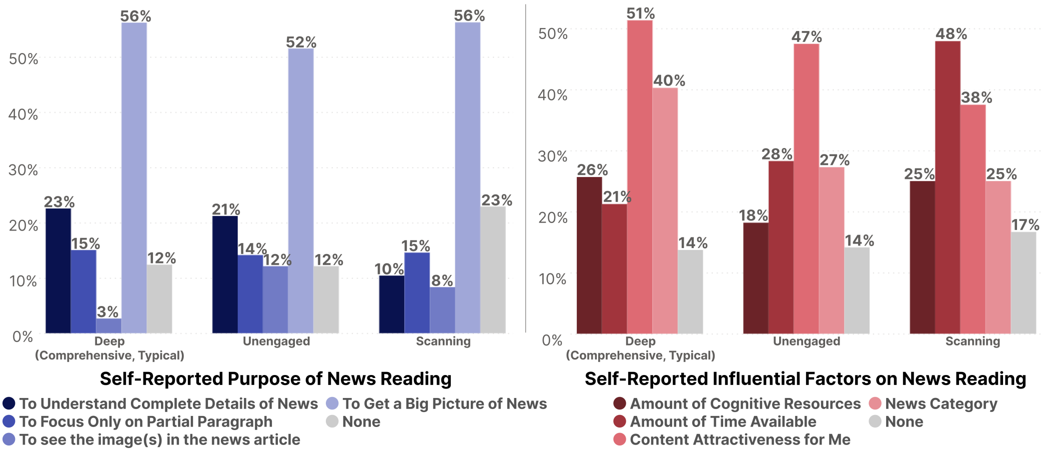


Fig. 8. The participants' self-reported purposes for reading pushed news (left), and the factors they said led them to choose their reading mode (right)

1.905, p = .056; for checking article's title, Z = 2.327, p = .020; and for reading entire article, Z = 3.182, p = .002).

We further looked into the differences in the likelihood of adopting deep reading among the three kinds of opportune moments; we did not see any significant differences (receiving vs checking-title: Z = 0.19, p = 0.85, receiving vs. reading-article: Z = -0.49, p = 0.62; checking-title vs reading-article: Z = -0.35, p = 0.73). This result suggests that, when participants entered the pushed news, the opportuneness of the moments perceived for these three kinds of opportune moments did not significantly differ in the impact on participants' likelihood to engage in deep reading.

We further examined which mode of shallow reading increased during inopportune moments, and we discovered that the lower overall likelihood of shallow reading at opportune moments was mainly due to a dramatic drop in the adoption of scanning mode at those moments. Scanning was at least four times more likely to be adopted at all three kinds of inopportune moments than at highly opportune ones, and these differences were all highly statistically significant (for receiving notification, Z = -3.55, p < .001; for checking article's title, Z = -2.627, p = .009; and for reading entire article: Z = -2.85, p = 0.004).

However, in sharp contrast to the above results, the unengaged reading mode was prevalent across both opportune and inopportune moments, adopted by 31.8% (n = 41) of participants during opportune moments for receiving notification, by 28.4% (n = 40) of them at opportune moments for checking article's title, and by 25.2% (n =36) of them at opportune moments for reading entire article, respectively. This result is important because it shows that participants were equally likely to adopt unengaged reading at opportune moments as they were at inopportune ones. To gain a better understanding of what influenced participants' adoption of a specific reading mode, we continue our examination of the reading purpose and factors that were associated with each reading mode in the next section.

4.3 Self-reported Influential Factors and Purposes in News Reading at (In)Opportune Moments

For each sampled pushed news, participants reported their purposes for reading the news article and the contextual factors they thought had influenced why they read the news in the chosen

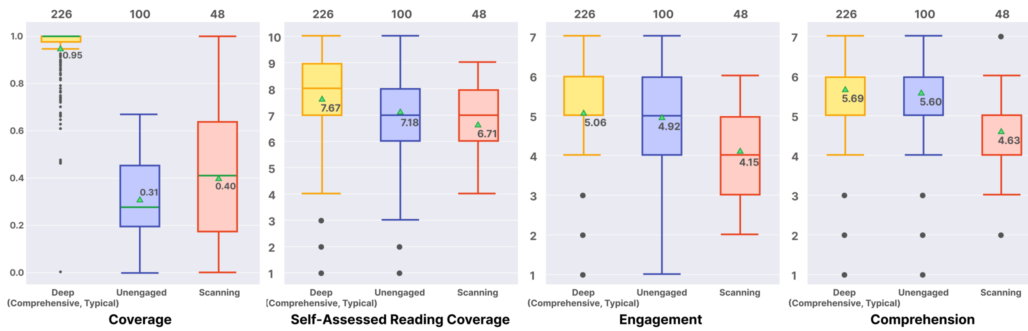


Fig. 9. Participants' logged coverage, assessment of their own coverage, engagement, and comprehension during each news-reading instance (The numbers of data points for each reading mode are displayed above the boxplot)

way. As shown in Figure 8 (left), for most reading modes, the main purpose of news reading was "to get a big picture of the news."; for all three reading modes, this purpose was chosen more than 50% of the time. In terms of influential factors, the most-mentioned factor when participants adopted the scanning reading mode was "the amount of time available", which was mentioned nearly half of the time (48%), significantly higher than when using other reading modes (Z = 2.07, p = 0.0385). In contrast, when adopting the unengaged reading mode, participants only mentioned this factor 28% of the time; the most commonly mentioned factor for this reading mode was "content attractiveness," which was mentioned nearly half of the time (47%), significantly more often than the other factors. (v.s. "amount of cognitive resources" Z = -4.26, $p < 0.001$; v.s. "amount of time" Z = -2.76, p = 0.006; v.s. "news category" Z = -2.91, p = 0.004; v.s. "None" Z = -4.84, $p < 0.001$). The spike in content attractiveness in Figure 8 was also evident in the unengaged reading mode among the shallow reading modes. These results suggest that the unengaged reading mode was more often associated with whether participant were interested in the news content, whereas the scanning reading mode was more often associated with participants' perception of time available in the moment.

4.4 Self-Assessed Reading Coverage, Engagement, Comprehension, and Perceived Credibility of Pushed News

Finally, to answer RQ3, we examined participants' self-reported reading coverage, engagement with, comprehension of, and credibility perception given to pushed news.

4.4.1 Self-Assessed Reading Coverage, Engagement, and Comprehension of Pushed News. As shown in Figure 9, while participants reported higher reading coverage of pushed news (on a 10-point rating scale, each step representing a 10% coverage increment) when using deep reading compared to unengaged ($t(364.5)$ = -2.23, p = 0.027) and scanning ($t(359)$ = -2.86, p = 0.0045) reading modes, overall, they reported high reading coverage across all reading modes (deep: M = 76.7%, SD = 19.5%, unengaged: M = 71.8%, SD = 19.5%, scanning: M = 67.1%, SD = 13.7%). Nevertheless, our analysis of the log data indicated that participants' actual reading coverage fell short of 50% around one-third of the time(32.7%). As shown in Figure 9, it is noticeable that participants often overestimated their reading coverage when using unengaged and scanning reading modes compared to logged coverage. Notably, they reported reading at least half the content in 92% of instances and 80% of the content in 49.5% of instances.

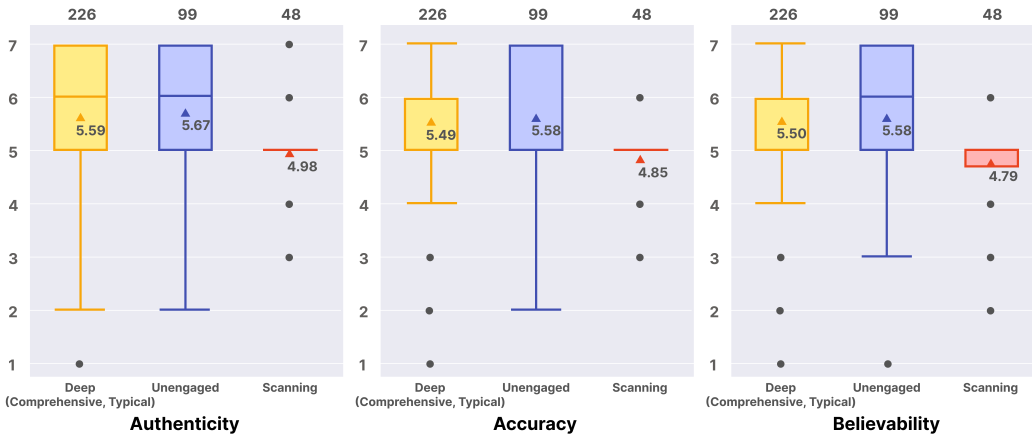


Fig. 10. Participants' self-reported perceptions of news items' credibility (The numbers of data points for each reading mode are displayed above the boxplot)

In terms of engagement, on the other hand, participants' self-reported engagement in reading when using the scanning reading mode (M = 4.15, SD: 1.07) was significantly lower than when using the other two reading modes (M = 5.02, SD: 1.31; $t(365.2)$ = -2.61, p=.009); similarly, participants' self-reported comprehension when using the scanning reading mode (M = 4.63, SD: 1.06) was also significantly lower than the other two reading modes (M = 5.66, SD: 1.13, $t(364.2)$ = -3.07, p=.002). These results again suggest a clear distinction between the scanning and unengaged reading modes, in that participants had similar perceptions of their own engagement with and comprehension of the sampled news when using the latter reading mode and deep reading, but their such perceptions were significantly lower when using the scanning reading mode.

4.4.2 Perceived Credibility of Pushed News. Figure 10 shows participants' crediblity assessments in three aspects, authenticity, accuracy, and believability. The results showed that participants' credibility perceptions of the sampled news articles were highly similar between unengaged reading (authenticity: M = 5.67, SD = 1.12, accuracy: M = 5.58, SD = 1.19, believability: M = 5.58, SD = 1.28) and deep reading (authenticity: M = 5.59, SD = 1.17, accuracy: M = 5.49, SD = 1.21, believability: M = 5.50, SD = 1.25). It is noteworthy that our results suggest lower perceived credibility when participants used the scanning reading mode compared to the other two modes (authenticity: M = 4.98 SD = 0.76, accuracy: M = 4.85 SD = 0.80, believability: M = 4.79 SD = 0.94). However, we only observed marginal statistical significance for authenticity but not for the other two credibility measures (authenticity: $t(368.8)$ = -1.91, p=.0565; Accuracy: $t(364.7)$ = -1.68, p=.0932; believability: $t(362.5)$ = -1.35, p=.177), making the difference in the self-assessed credibility of news among the reading modes inconclusive. However, it is likely that the relatively small sample of instances using the scanning reading mode may have reduced the statistical power for detecting such a difference [2]. We believe that future research can investigate this aspect further to provide more robust findings.

5 DISCUSSION

5.1 Opportune Moment for Pushed News Delivery on Smartphones

Our results confirmed that when our participants received pushed news at opportune moments, they were more likely to adopt deeper reading modes – i.e., read the pushed news more thoroughly

– than they were when they received such news at inopportune ones. This result establishes a connection between opportune moments for reading news and the style of processing, which prior research has not yet established. In line with the goal of encouraging users of mobile news apps to process news more deeply [41], this result suggests that it would be beneficial for news apps to send pushed news notifications primarily at moments perceived as opportune for processing news to promote deep processing of the news. This delivery strategy is straightforward, but it fundamentally differs from the approach of sending news notifications at any time without considering whether the recipient is able to read them thoroughly at that moment. The latter delivery strategy might be effective – and sometimes, preferable – for notifications that users want to process step-by-step, such as when they want to know about their existence first and respond to them later, a common multi-stage notification-response process that has been observed and discussed in notification research [94]. Nevertheless, results from this study showed that even if participants did not read a pushed news notification right away but instead read it later when browsing the notification drawer, it did not increase the likelihood of deep news reading. Additionally, our results indicate that the likelihood of participants thoroughly reading pushed news was not significantly different across opportune moments for each response stage. These results imply that the strategy of sending news notifications at any moment and expecting users to engage with the news content in-depth when they have the chance to check the notifications may not actually increase the likelihood of deep reading. Based on these results, dividing the process of interacting with push news notifications into multiple steps may not increase readers' engagement in deep reading; this is because the times at which people receive pushed news notifications may not always coincide with the times when they are able to deeply process the news. This implies that it is vital to detect opportune moments not simply for news reading, but for *deep news reading*, in order to reduce the prevalence of superficial processing of the content of pushed news. Therefore, we encourage future researchers and news app developers to continue building models for identifying opportune moments for deep news reading, taking into account the time available for users to fully process news articles. On the other hand, our findings suggest that identifying opportune moments may not, by itself, help reduce the prevalence of the unengaged reading mode, as this mode was not related to the perceived opportuneness of the moment for reading news. Therefore, this implies that future research should explore other ways to reduce the prevalence of unengaged reading, such as improving reader engagement. Finally, it is important to acknowledge that this study did not definitively establish a direct link between opportune moments for reading news and detecting misinformation. As we did not perform any fact-checking on the news sampled by the ESM, we cannot conclude whether the sampled news contained misinformation or not. While prior research has indicated a connection between processing style and the ability to detect misinformation [79], further research is needed to confirm the potential impact of opportune moments on the success of detecting misinformation.

5.2 News Reading Patterns on a Mobile News App vs. on Desktop

Although we identified a similar number of reading modes using the viewport and a comparable clustering technique, our findings on the patterns of news reading modes around a smartphone news app differed from those identified by previous research conducted on desktops [48] or across multiple devices (mobile and non-mobile devices) [36]. For example, the two longest reading modes in Grinberg's [36] study, "shallow" and "idle", were absent in our study; "scan", the shortest reading mode identified from his study, was also on average longer than all of our reading modes except comprehensive reading. In contrast, our two shallow reading modes' average dwell time was considerably shorter compared to these two studies, averaging about 11 and 5 seconds, respectively, much shorter than all of the reading modes in Grinberg's [36] study and Lagun and Lalmas's [48] study except their "Bounce" mode, a mode similar to our unengaged mode, the reader reading limited coverage of the news and quickly leaving. However, Lagun and Lalmas's [48] study did not identify the scanning reading mode, characterized by quickly skimming the entire article. Notably, although the pattern of skimming news was identified in both our study and Grinberg's [36] study, the dwell duration of their "scan" was significantly longer (24 seconds vs. 4.86 seconds). Future research could investigate whether the mindset of and the cause of the adoption of these two reading patterns are similar.

While numerous factors could contribute to the differences between our set of reading modes and those identified in previous works, we suspect that the involvement of desktop reading in the dataset could be one of the contributing factors. In particular, the fact that two long reading modes in Grinberg's [36] study, "shallow" and "idle", were absent in our study to some extent can be explained by the frequent task-switching on mobile. That is, while these two modes indicate the readers stay in the news page for several minutes with very limited interaction with and coverage of the news, our participants rarely exhibited this behavior. This is likely because, if they decided not to read the news, they more often switched to other pages or apps instead of remaining in the news articles, thus exhibiting the unengaged reading mode in our study. When the participants dwelled in the page longer, it was mainly because they read the news thoroughly (i.e., comprehensive reading) rather than merely dwelling on the page. As a result, our dataset has little reading behavior displaying long dwell time but limited page coverage. Another possible reason is that participants' news reading on mobile phones was often triggered by notifications, which could occur at any time, including when they did not have enough time for reading.

5.3 The Two Distinct Shallow Reading Modes: Unengaged vs. Scanning

Finally, among the four reading modes identified in our study, we believe that the two shallow reading modes deserve more research attention. These two modes, which made up a significant proportion of logged news reading (40%), demonstrated quick and incomplete processing of news articles, a processing style that has been previously linked to a lower likelihood of detecting misinformation [79]. In addition, they exhibited differences in their objective properties, associated triggers that resulted in their choice of particular reading modes, prevalence, and self-rated reading engagement and comprehension. Specifically, we found that unengaged reading yielded the least amount of content, but when adopting this mode, participants were optimistic about their engagement with and understanding of the news, and perceived it as credible, to the same extent as when using deeper reading modes. One possible explanation for these results is that the participants were highly engaged in their reading at the start of the news article and, as a result, believed they had understood the article and chose not to continue reading. This explanation could be partially supported by the result that the adoption of reading mode was more likely to be associated by the participants with the attractiveness of the content. Probably because the main influential factor that results in this reading mode is interest in the content, unengaged reading was observed to be common at both opportune and inopportune moments. In contrast, scanning was found to be more likely to occur at inopportune moments, at least four times more compared to opportune ones, and probably due to this, participants often associated their adoption of this reading mode with perceived time availability rather than content. Participants also tended to rate their engagement and comprehension as lower when using this mode than when using other modes. And when news reading took place at opportune moments, the amount of scanning reading considerably decreased and the amount of deep reading increased. This observed change largely supports that the adoption of scanning reading was more often associated with the opportuneness of the timing, whereas the adoption of unengaged reading was more often associated with content.

All in all, these results indicate a clear distinction between the scanning and unengaged reading modes. While we cannot definitively determine the reasons for the differences between unengaged and scanning modes, these differences are notable in many ways and warrant further research. It is crucial to distinguish between these two shallow reading modes because it implies that identifying opportunities for news reading possibly only reduces the likelihood of scanning, but not unengaged reading. However, there are also several questions that require further research and clarification, such as whether the two shallow reading modes represent different levels of misinformation risk for readers, and how to address unengaged reading that is prevalent across various contexts. Clarifying the relationship between the opportuneness of the moment, likelihood of detection of misinformation, and reading patterns would be necessary for future research. Also, our concept of reading mode was based on the objective properties of these reading patterns, as logged on a news app, and did not consider the participants' actual reasons for why they read or skipped news content. Clarifying this would also help future research to understand the relationship. That being said, regardless of the reason, while we would not know exactly why the participants skipped news content, skipping and skimming news content may not always be desirable, such as when an article contains misinformation in its later part and is shared by the reader without that part being read. When an article is suspected of containing misinformation, it may be beneficial to remind users to be cautious in their reading and sharing of the article.

6 RESEARCH LIMITATIONS

The current study has several limitations that should be taken into account when interpreting the results. First, the participants were young Taiwanese Android users, which limits the generalizability of the findings to other demographics and regions with different news industry structures. This is a common limitation in studies about mobile behaviors [15]. Second, our focus on identifying opportune moments for pushed news led to a limited dataset that could include only the news reading instances associated with an ESM response. Consequently, we analyzed only a partial dataset. Furthermore, the restricted dataset contained a mere 10.2% of instances representing the scanning reading mode. This limited sample size could have affected the study's statistical power, potentially hindering our ability to detect certain significant differences, such as self-assessed credibility, which exhibited only marginal significance in the results obtained. Although the number of participants in our study was typical for mobile experience sampling research [96], the scarcity of data related to the scanning reading mode diminished the statistical significance of some findings. Nonetheless, we observed notable trends in the data. Third, we did not conduct fact-checking on the news sampled in the ESM, as carrying out this task in an in-the-wild study was infeasible due to the limited resources of fact-checking institutions in our country. This limitation prevented us from exploring the relationship between the perceived opportuneness of the moment and the belief in or likelihood of detecting misinformation in the sampled news articles. It is possible that the sampled news, despite being collected from official news websites, might contain inaccurate information, which could have influenced participants' perception of news credibility. Future research may consider implementing a field experiment that involves the dissemination of news containing misinformation to investigate this relationship more comprehensively. Fourth, the results of this study do not permit us to claim generalizability to other types of reading material (e.g., blog articles, social media posts) or media content consumption, as users' purposes for consuming and engaging in different types of media content may be fundamentally different. Fifth, it is possible that reading behaviors, such as the number of scrolls, may have been influenced by differences in screen size and article length; however, these factors were not considered in our analysis. Sixth, the sampling method used in this study may have oversampled receptive moments, potentially skewing the results towards moments when participants were more receptive to push notifications. To address this issue, we allowed participants to answer news notifications that occurred within 30 minutes prior to the sampled moment in an attempt to capture more unreceptive moments. This resulted in only a slightly different distribution of reading modes between moments when an ESM questionnaire was issued and when it was not. However, our ESM still contained a relatively higher number of questions, which suggests that it was likely to oversample receptive moments.

7 CONCLUSION

In this study, we developed a news aggregation app called NewsMoment and utilized experience sampling to investigate the behavior of NewsMoment users when reading pushed news. Our results show that timing for pushed news mattered; opportune moments for receiving pushed news notifications were positively associated with deeper news reading. Additionally, opportune moments for reading entire news articles were similar to those for receiving notifications and checking article titles in terms of the likelihood of deep news reading. These findings suggest that a multi-stage notification process may not be the most effective approach for encouraging in-depth news reading, and instead, it is important to detect opportune moments specifically for deep news reading. Our results also revealed two distinct shallow reading modes, one of which, the unengaged reading mode, was prevalent regardless of the opportune moment, whereas the other, the scanning reading mode, was more likely to occur at inopportune moments than opportune ones. This highlights the importance of identifying opportune moments for news reading, primarily to reduce the likelihood of users adopting a scanning reading mode, which may be more likely due to insufficient time to process the news. However, this approach might not be effective for reducing the unengaged reading mode. To address this, further exploration is needed.

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